Models and Managers:
The Concept of a Decision Calculus

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ABSTRACT

A manager tries to put together the various resources under his control into an activity that achieves his objectives. A model of his operation can assist him but probably will not unless it meets certain requirements. A model that is to be used by a manager should be simple, robust, easy to control, adaptive, as complete as possible, and easy to communicate with. By simple is meant easy to understand; by robust, hard to get absurd answers from; by easy to control, that the user knows what input data would be required to produce desired output answers; adaptive means that the model can be adjusted as new information is acquired; completeness implies that important phenomena will be included even if they require judgmental estimates of their effect; and, finally, easy to communicate with means that the manager can quickly and easily change inputs and obtain and understand the outputs.

Such a model consists of a set of numerical procedures for processing data and judgments to assist managerial decision making and so will be called a decision calculus. An example, ADBUDG II is described. This is an on-line model for use by product managers on advertising budgeting questions. The model is currently in trial use by three product managers.

1. Introduction

The big problem with management science models is that practically nobody uses them. This is especially true in marketing. There have been a few applications, of course, but the practice is a pallid picture of the promise.

The incentives for successful implementation are great. John F. Kennedy has been quoted as saying

> "The real issue today is the management of industrial society [1]."

Few who read the newspapers can disagree. Marketing is of particular interest, not only because of its key and sometimes controversial role in the society, but also because fundamental knowledge here has application beyond business into the marketing-like activities of governments, universities, hospitals, and other organizations.

Although there are many facets to successful implementation, the one to be taken up here is the meeting between manager and model. I believe that communication across this interface is almost nil and that this fact stands as a major impediment to successful use of marketing models. Furthermore I want to suggest that the requirements of the interface have strong implications for the design of the model itself.

The paper is organized under the following headings: (1) Introduction (2) What's wrong? (3) How do managers use models? (4) What might be right? (5) An example: ADBUDG II (6) What about science? and (7) Discussion.

The example to be discussed comes from marketing, in fact advertising, but most of the issues appear to be general to the manager-model interface. Consequently, at the risk of sometimes being rather abstract, the discussion will be kept general.

The terms "manager" and "decision" will be used frequently. Let it be noted now that a "manager" is frequently a fuzzy, shifting mix of people and a "decision" is usually a murky event, identifiable only in retrospect.

2. What's Wrong?

Some of the reasons that marketing models are not used more widely appear to be:

(1) Good models are hard to find. Convincing models that include the company's control variables and so contain direct implications for action are relatively difficult to build. Some progress, however, is certainly being made.

(2) Good parameterization is even harder. Measurements and data are needed. They require high quality people at the design stage and are often expensive to carry out.

(3) Managers don't understand the models. People tend to reject what they do not understand. The manager carries responsibility for outcomes. We should not be surprised if he prefers a simple analysis that he can grasp, even though it may have a qualitative structure, broad assumptions, and only a little relevant data, to a complex model whose assumptions may be partially hidden or couched in jargon and whose parameters may be the result of obscure statistical manipulations.

Typically the manager is willing and eager to accept flawless work that delivers the future to him with certainty. Unfortunately as he digs into any study performed by human researchers in an ordinary OR group, he finds assumptions that seem questionable, confusing terminology, and a certain tendency to ignore a variety of qualitative issues the manager feels are important. The manager feels that to get deep into the model and find out what is really going on is totally out of the question because he lacks the background. The solution to this predicament is often for him to pick on some seeming flaw in the model, usually a consideration left out, and make that the basis for postponing use into the indefinite future.

In this situation the operations researcher's response is often to conclude that his model is not complete enough. Therefore he goes back to work to make things more complicated and probably harder to understand. Meanwhile the manager continues to use intuitive models that are much simpler than the one rejected.

I might point out the professional OR/management science fraternity also escalates the model builder into complexity. A favorite pastime in the trade is to tell a model builder, "You left such and such out."

(4) <u>Most models are incomplete</u>. Having just decried complexity as a bar to understanding, I now decry incompleteness. This means that I hope we can invent simple models that have the capacity to include quite a few phenomena.

Incompleteness is a serious danger if a model is used for optimization. Optimization may drive control variables to absurd values if critical phenomena are omitted. One popular answer to this problem is not to optimize. Sometimes this is the right thing to do - we should say out loud the model provides only part of the decision making information and that the rest must come from elsewhere. However, in most cases we want to be able to evaluate and compare. This is embryonic optimization and incompleteness can be a pitfall.

The above list of obstacles of implementation could be extended but should suffice to ward off complacency.

3. How do managers use models?

Here is an impression, albeit anecdotal, of how managers actually use models.

The OR Group of a major oil company recently did a survey on the use of mathematical programming in production scheduling at their refineries. Refinering scheduling was a pioneer application of mathematical programming and has been an active research area for 10-15 years. At one refinery the dialog between the interviewer and the local OR analyst went somewhat as follows:

Interviewer: "Do you make regular mathematical programming runs for scheduling the refinery?"

Analyst: "Oh yes."

Interviewer: "Do you implement the results?"

Analyst: "On no!"

Interviewer: "Well, that seems odd. If you don't implement the results, perhaps you should stop making the runs?"

Analyst: "No. No. We wouldn't want to do that!"

Interviewer: "Why not?"

Analyst: "Well, what happens is something like this: I make several computer runs and take them to the plant manager. He is responsible for this whole multi-million dollar plumber's paradise."

"The plant manager looks at the runs, thinks about them for a while and then sends me back to make more. I do this and bring them in. He looks at them and probably sends me back to make more runs.

"This process continues until, finally, the plant manager screws up enough courage to make a decision."

Next let me recount some experiences with people using MEDIAC [2] a media planning model developed by Len Lodish and myself. The first step in using the model is preparing the input data. This requires a fair amount of reflection on the problem at hand, a certain amount of digging out numbers, and usually some subjective estimates of several quantities. Thereafter, the model is run and a schedule is generated.

The user looks at the schedule and immediately starts to consider whether it makes sense to him or not. Is it about what he expected? Sometimes it is and, if so, usually that is that. Oftentimes, however, the schedule does not quite agree with his intuition. It may even differ substantially. Then he wants to know why. A process starts of finding out what it was about the inputs that made the outputs come out as they did. This usually can be discovered without too much difficulty by a

combination of inspection, consideration of how the model works, and various sensitivity analyses.

Having done this, the user decides whether he is willing to go along with results as they came out. If not, he can, for example, change the problem formulation in various ways or possibly change his subjective estimates. Sometimes he finds outright errors in the input data. Most of the time, however, if he has been careful in his data preparation, he will agree with the reasons for the answers coming out as they did and he has, in fact, learned something new about his problem. The whole process might be described as an updating of his intuition. The model has served the function of interrelating a number of factors and, in this case, not all the implications of the interrelations were evident to him when he started.

Notice, incidentally, that he has by no means turned over his decision making to the computer. He remains the boss and demands explanations from his "subordinate."

I believe the same type of process is going on with the plant manager in the earlier example. I see the whole analysis-education-decision process as a man-model-machine interaction in which the man does not lose responsibility or control and instead of understanding less understands more.

Such an interaction should, I believe, be the goal for much of our normative model building.

4. <u>What might be right?</u>

If we want a manager to use a model, we should make it his model, an extension of his ability to think about and analyze his operation. This puts special requirements on design and will often produce something rather different from what a management scientist might otherwise build. We propose a name to describe the result. A <u>decision calculus</u> will be defined as a model-based set of procedures for processing data and judgments to assist a manager in his decision making.

From experience gained so far, it is suggested that a decision calculus should be:

(1) <u>Simple</u>. Simplicity promotes ease of understanding. Important phenomena should be put in the model and unimportant ones left out. Strong pressure often builds up to put more and more detail into a model. This should be resisted, at least until people demonstrate they can understand and use relatively simple models.

(2) <u>Robust</u>. By this it is meant that a user should find it difficult to make the model give bad answers. This can be done by a structure that inherently constrains answers to sensible values.

(3) <u>Easy to control</u>. A user should be able to make the model behave the way he wants it to. For example, he should know how to set inputs to get almost any outputs. This seems to suggest that the user could have a preconceived set of answers and simply fudge the inputs until he gets them. That sounds bad. Should not the model represent objective truth?

Wherever objective accuracy is attainable, I feel confident that the vast majority of managers will seize it eagerly. Where it is not, which is most of the time, the view here is that the manager should be left in control. Thus, the goal of parameterization is to represent the operation as the manager sees it. I rather suspect that if the manager cannot control the model he will not use it for fear it will coerce him into actions he does not believe in. However, I do not expect the manager to abuse the capability because he is honestly looking for help.

(4) Adpative. The model should be capable of being updated as new information becomes available. This is especially true of the parameters but to some extent of structure too.

(5) Complete on important issues. Completeness is in conflict with simplicity. Structures must be found that can handle many phenomena without bogging down. An important aid to completeness is the incorporation of subjective judgments. People have a way of making better decisions than their data seem to warrant. It is clear that they are able to process a variety of inputs and come up with aggregate judgments about them. So, if you can't lick 'em, join 'em. Subjective estimates will be valuable for quantities that are difficult to measure or which cannot be measured in the time available before a decision must be made.

One problem posed by the use of subjective inputs is that they personalize the model to the individual or group that makes the judgments. This makes the model, at least superficially, more fragile and less to be trusted by others than, say a totally empirical model. However, the

model with subjective estimates may often be a good deal tougher because it is more complete and conforms more realistically to the world.

(6) Easy to communicate with. The manager should be able to change inputs easily and obtain outputs quickly. On-line, conversational I/O and time-shared computing make this possible.

Every effort should be made to express input requests in operational terms. The internal parameterization of the model can be anything, but the requests to the user for data should be in his language. Thus, coefficients and constants without clear operational interpretation are to be discouraged. Let them be inferred by the computer from inputs that are easier for the user to work with.

On-line systems come through as being very effective in bringing the model to the manager. Some writers have belittled the importance of this. They argue that decisions made once a year or even once a month hardly require systems that deliver the answers in ten seconds. Anyone who has used a conversational system perceives that this argument misses the point. Practically no decision is made on a single run of a model. A person develops his understanding of a problem and its solution as he works on it. The critical time is not that of the decision deadline but of the next step in the user's thinking process.

Perhaps equally as important as the operational convenience of conversational programs is their contribution to learning. Good on-line models are self-instructing and introduce a person to the issues of the problem and the model much faster than would otherwise be possible.

A user can rapidly get a feel for how the model works through personal use. This is in sharp contrast to batch processing with its long time lags and imposing tribal rituals of punched cards, systems programmers and computer operators.

In summary, we are learning techniques of model design and implementation that bring the model to the manager and make it more a part of him. We are calling such a model a decision calculus.

5. An Example: ADBUDG II

An on-line marketing-mix model for use by product managers is currently being developed.

The product manager is an ideal customer for a decision calculus. He has substantial responsibility for the whole marketing-mix of control variables. He is busy and will not use a model unless it does something for him. He is at ease making judgments and, being a single person accountable for results, he can gather inputs and make judgments without the elaborate coordination required in most complex decision processes.

The work is being done in cooperation with three different product managers at two different companies. The variety in companies and managers is helpful for getting perspective on the man-model interface and in keeping the model structure general.

The development is being done in evolutionary steps. First a very simple advertising budgeting model was brought up and used to demonstrate concepts. This was called ADBUDG. Then a somewhat more complex model for advertising budgeting, one with sufficient detail to

be of practical value, was brought up and is currently in use. This is ADBUDG II and will be described below. Experience with it will be used in designing more complex models to be called BRANDAID I and BRANDAID II.

5.1 Model structure. We have said we wanted a simple, robust, easy to control model of sales response to advertising.

As a first step brand sales is partitioned into product class sales and brand market share. Such a breakdown has a number of advantages, not the least of which is that marketing people think this way.

Consider a given time period. We next suppose:

1. If advertising is cut to zero, brand share will decrease, but there is a floor, min, on how much share will fall in one time period.

2. If advertising is increased a great deal, say to something that could be called saturation, brand share will increase but there is a ceiling, max, on how much can be achieved in one time period.

3. An estiamte can be made by data analysis or subjective judgment of the effect on share in one period of a 50% increase in advertising.

4. Share under current advertising rate is known.

We now have four points on a brand share response to advertising curve. A smooth curve can be put through them. See Figure 1.

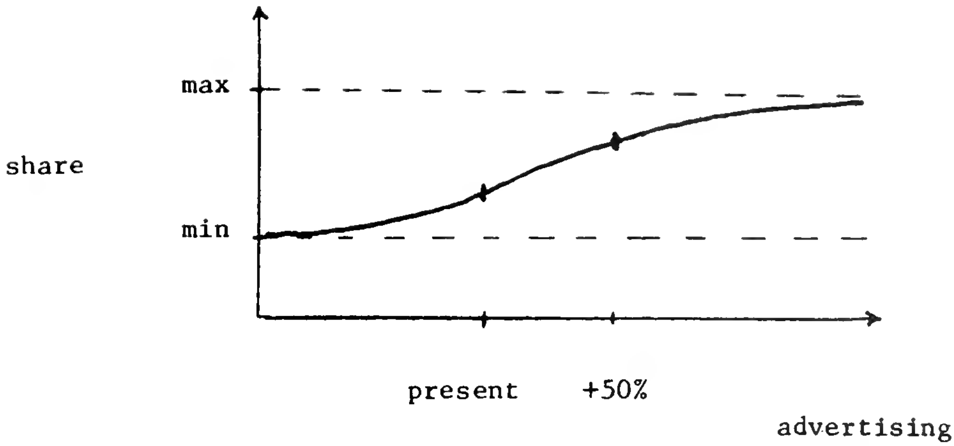

Figure 1. A smooth curve of share vs. advertising is put through two points and two asymptotes.

The curve presently used is

$$\text{share} = \min + (\max - \min)\,\frac{(\text{adv})^{\gamma}}{\delta + (\text{adv})^{\gamma}} \tag{1}$$

The constants δ and γ are uniquely determined by the input data.

Equation (1) represents a restricted set of response relations. Actually I am willing to use anything. The curve could go down or up or loop the loop for all I care. It should be changed when and if a product manager wants it changed. Meanwhile, he can give four numbers, each of which has operational meaning to him and which together will specify a curve. If he gives reasonable numbers, the curve will give back reasonable answers. Furthermore, four numbers are about at the limit of our ability to parameterize sales response today.

I claim the relationship is robust. Suppose we do a two level spending test and run a regression that is linear in advertising in order to estimate response. This might make reasonable statistical

sense but by itself would have absurd normative implications (advertising = 0 or ∞). However, if we use the regression results to estimate the +50% point and choose a reasonable max and min we can expect reasonable answers. This is not something that can be proved in general, but with a specific manager and product it can be established by sensitivity analysis.

Incidentally, the sketch in Figure 1 shows an S-shaped curve. This is not required by (1). If $\gamma > 1$, the curve will be S-shaped, for $0 < \gamma \leq 1$,a concave function. The particular γ will depend on the input data.

The model above is essentially the one used in the original ADBUDG. A major lack in the model is the consideration of time effects. To consider these we assume:

1. In the absence of advertising, share will decay a constant percentage in each time period, i.e. decay is exponential.
2. This decay determines min in any time period.
3. (max-min) stays constant with time.

Let <u>decay</u> denote the decay constant. Under the above assumptions

$$\text{decay} = \text{min/current share}$$

$$\text{min}(t) = \text{decay} * \text{share}(t-1)$$

$$\text{share}(t) = \text{decay} * \text{share}(t-1) + (\text{max-min}) \frac{[\text{adv}(t)]^{\gamma}}{\delta + [\text{adv}(t)]^{\gamma}} \qquad (2)$$

This is a simple dynamic model. It is understandable and it behaves reasonably. It can be further generalized by permitting some of the constants to change with time, but that does not seem desirable at the moment.

But now what is meant by advertising? Dollars? Exposures? A product manager worries about spending levels, media, and copy. Let us construct two time varying quantities:

1. A media efficiency index.
2. A copy effectiveness index.

Both will be assumed to have reference values of 1.0. We now hypothesize that the delivered advertising, i.e. the adv(t) that goes into the response function is given by

adv(t) = media effcy(t) * copy effct(t) * dollars(t)

The media efficiency and copy effectiveness indices can be determined subjectively, but much better alternatives exist. Copy testing is helpful and media data on cost, exposures by market segment, and relative value of market segments can be used to develop a media index.

So far we have included: advertising response, media efficiency, copy effectiveness, and share dynamics. Consider next product class sales. They may respond to advertising and have dynamics. The treatment in the model is essentially the same as that for share and so we omit the details.

A variety of other factors affect brand share and sales and therefore indirectly or directly advertising budgets. Some of these factors are: sales trends in the product class, seasonality, promotions, competition, distribution changes, price, product changes, and package changes. Any or all of these items may affect the product manager's thinking about advertising.

We propose to treat these factors but in a simple way, not unlike the way a product manager might handle them now. Later models will treat them in more detail.

Consider first sales trends and seasonality. We break out the product class component (which is frequently most of the effect) and construct an index by each time period.

Turning next to the other factors, we find that the product manager has a definite idea about what various changes are likely to do for him. If he plans a promotion he does so with the expectation that something will happen to his sales and share. The same holds for a product change or price change. Therefore we can ask him to construct an index of how he thinks these factors will affect brand share in each period. The process can be formalized by filling in a table such as the following with all factors deemed by the product manager to be relevant.

Index of effect on share — Period	1	2	3	4
promotions	1.00	1.10	.98	1.00
price	1.00	1.00	1.00	1.00
package	1.00	1.05	1.05	1.05
competitive action	1.00	.98	.95	1.00
other	1.00	1.00	1.00	1.00
composite	1.000	1.132	.978	1.050

Table 1. Developing a composite index of non-advertising effects

The composite index of non-advertising effects is simply the product of the numbers in each column.

To summarize the model:

1. Share

share(t) = non-adv effect index(t) * raw share(t)

$$\text{raw share}(t) = \text{decay} * \text{raw share}(t-1) + (\text{max}-\text{min}) \frac{[\text{adv}(t)]^{\gamma}}{\delta + [\text{adv}(t)]^{\gamma}}$$

adv(t) = media effcy(t) * copy effct(t) * adv dollars(t)

2. Brand Sales

brand sales(t) = product class reference sales * product class sales index(t) * share(t)

3. Profits

contribution to profit after adv(t) = contribution per sales unit(t) * brand sales(t) - adv dollars(t)

The units situation has not been developed in detail and we have omitted the effect of brand advertising on product class sales, but otherwise the above represents the current status of ADBUDG II.

5.2 Conversational I/O. We have said that the model should be easy to use. It must be easy to put data into the computer, easy to find out what is in there, easy to change it, easy to make output runs, easy to search over control variables and make sensitivity analyses. Clerical errors should be quickly correctable. The mechanical operating details should require as little training as possible.

The best way to show how we are approaching these issues is by demonstration. Short of that we can provide an example. Table 2 shows input data for "Groovy" a struggling brand in the treacle market Table 3 shows the trace of the data input questions used to generate Table 2. Table 4 shows an output run.

A few explanatory notes on the input data of Table 2:

1. The advertising response parameters are deduced from the reference case data. Periods A and B are two consecutive periods, possibly hypothetical but in any case defined by the user. The data for A and B uniquely determine the sales response and decay constants. See also the questions in Table 3.

2. In this example brand advertising is assumed to have no appreciable effect on product class sales.

3. The letter "M" is used to denote "millions."

The trace of input in Table 3 is reasonably self-explanatory. A few notes on the output of Table 4 are:

1. SLOPE is an aid to searching over brand advertising. It is intended to answer the question that a user is most likely to ask: Which way should I change advertising to increase profit? But we must ask: What profit? Profit in that period or,since sales changes persist into the future, profit over several periods? We have chosen to anticipate the answer to be "cumulative contribution after advertising" in the last period of the calculation. But which advertising? We expect the question might be asked about advertising in any period. Thus we calculate

SLOPE(t) = the change in cumulation contribution after advertising in last period per unit change in adv dollars (t)

```
/GROOVY-69/

 1 BRAND NAME: GROOVY
 2 NO. PERIODS: 4.000
 3 PER. LENGTH:QUARTER
 4 FIRST PER.: 1ST 69
 5 AREA: US
     REFERENCE CASE - BRAND
 7 PER. A SHARE (% OF UNITS):  1.860
 8 PER. A ADV (DOL./PER.):  .486M
 9 PER. B MIN SHARE:  1.770
10 PER. B MAX SHARE:  2.250
11 PER. B WITH + 50% ADV:   1.950
12 LONG RUN MIN SHARE:    .000
14 MEDIA EFFCY: 1.000
15 COPY EFFECT: 1.000
16 SALES UNIT: HOGSHEADS
17 CONTRIBUTION (DOL./UNIT):    .680
18 BRAND PRICE (DOL/UNIT):  1.812
     OTHER BRAND DATA
19 STARTING SHARE: 1.860
     REFERENCE CASE - PROD. CLASS
21 PROD. CLASS NAME: TREACLE
22 PER. A CLASS SALES (UNITS/PER.):   290M
29 CLASS PRICE (DOL/UNIT):  1.880
     TIME VARIATIONS
     PERIOD          1      2      3      4
30 CLASS SALES INDEX:
                   .943  1.012  1.065   .959
31 NON-ADV EFFECT INDEX:
                  1.000  1.030  1.000  1.000
32 MEDIA EFFCY:
                  1.000  1.000  1.000  1.000
33 COPY EFFECT:
                  1.000  1.000  1.000  1.000
34 CONTRIBUTION (DOL/UNIT):
                   .680   .680   .680   .680
35 BRAND PRICE (DOL/UNIT):
                  1.812  1.812  1.812  1.812
36 CLASS PRICE (DOL/UNIT):
                  1.880  1.880  1.880  1.880
37 BRAND ADV (DOL./PER.):
                  .486M  .606M  .876M  .414M
```

Table 2. Summary of input data for Groovy brand. It has been stored in a file named /GROOVY-69/.

```
@GO /ADBUDG II/

ADBUDG II - A MULTIPERIOD ADVERTISING BUDGETING MODEL

1 COMPUTER ASKS QUESTIONS IN STANDARD FORM
2 COMPUTER ASKS QUESTIONS IN SHORT FORM
ANS=1

1 ENTER NEW DATA
2 USE SAVED DATA
ANS=1

BRAND NAME: GROOVY

NO. OF TIME PERIODS(MAX=8):4

LENGTH OF PERIOD: QUARTER

NAME OF FIRST PERIOD:1ST 69

GEOGRAPHIC AREA:  US

  BRAND DATA FOR REFERENCE CASE. TWO CONSECUTIVE PERIODS,
  CALLED A & B, WITH SEASONALITY,TREND,OR OTHER NON-ADV.
  EFFECT REMOVED.

MARKET SHARE IN PERIOD A (% OF UNITS): 1.86

ADVERTISING RATE IN PERIOD A (DOLLARS/PERIOD):  486000

MARKET SHARE IN PERIOD B IF ADVERTISING REDUCED TO ZERO
IN PERIOD B:1.77

MARKET SHARE IN PERIOD B IF ADV INCREASED TO SATURATION
IN PERIOD B:2.25

MARKET SHARE IN PERIOD B IF ADV IN PERIOD B INCREASED
50% OVER PERIOD A:1.95

MARKET SHARE IN LONG RUN IF ADV REDUCED TO ZERO:0

INDEX OF MEDIA EFFICIENCY (E.G. AVERAGE EFFICIENCY=1.0): 1.0

INDEX OF COPY EFFECTIVENESS (E.G. AVERAGE COPY=1.0):  1.0

UNITS IN WHICH SALES ARE TO BE MEASURED
(TO BE USED FOR BOTH BRAND AND PRODUCT CLASS.
E.G.,POUNDS,GALLONS,CASES,THOUSANDS OF DOLLARS,ETC.): HOGSHEADS

CONTRIBUTION PROFIT (EXCLUSIVE OF ADV EXPENSE)
EXPRESSED IN DOLLARS/SALES UNIT: .68

AVERAGE BRAND PRICE (DOLLARS/SALES UNIT): 1.812
```

Table 3. Trace of a user putting input data for Groovy into the computer. All user responses are circled.

```
MARKET SHARE AT START OF PERIOD 1:  1.86

  PRODUCT CLASS DATA FOR REFERENCE CASE. TWO CONSECUTIVE TIME
  PERIODS,A & B WITH SEASONALITY,TREND AND OTHER NON-ADV
  EFFECTS REMOVED.

NAME OF PRODUCT CLASS:  TREACLE

PRODUCT CLASS SALES RATE IN PERIOD A
  (UNITS/PERIOD): 290000000

CONSIDER RESPONSE TO PRODUCT CLASS ADV ?  NO

AVERAGE PRICE FOR PRODUCT CLASS (DOLLARS/SALES UNIT): 1.88

  TIME VARYING DATA. IF TIME VARIATION NOT SPECIFIED,
  REFERENCE DATA WILL BE COPIED INTO ALL PERIODS.

PRODUCT CLASS SALES RATE HAS SEASONAL OR OTHER NON-ADV
TIME EFFECT ? YES

INDEX OF PRODUCT CLASS SALES (REFERENCE CASE=1.00) FOR PERIOD:
1: .943
2: 1.012
3: 1.065
4: .959

BRAND SHARE HAS A NON-ADV TIME EFFECT ?YES

INDEX OF NON-ADV EFFECTS (REFERENCE CASE=1.00) FOR PERIOD
1: 1.0
2: 1.03
3: 1.0
4: 1.0

MEDIA EFFICIENCY VARIES ?  NO

COPY EFFICIENCY VARIES ?NO

CONTRIBUTION VARIES ?NO

AVERAGE BRAND PRICE VARIES ?  NO

AVERAGE PRICE FOR PRODUCT VARIES ?  NO

BRAND ADV RATE VARIES ? YES

BRAND ADV (DOLLARS/UNIT) IN PERIOD
1: 486000
2: 606000
3: 876000
4: 414000

1 SAVE DATA
2 PRINT DATA
3 CHANGE DATA
4 OUTPUT
5 RESTART
ANS=1

DATA FILE NAME: GROOVY-69
```

1 OUTPUT FOR	GROOVY			
2 PERIOD LENGTH:	QUARTER			
3 STARTING PERIOD:	1ST 69			
4 AREA:	US			
5 SALES UNIT:	HOGSHEADS			
6 DATA FROM FILE:	/GROOVY-69/			
8 PERIOD	1	2	3	4
9 MARKET SHARE: (% OF UNITS)	1.860	1.961	2.043	2.009
10 PROD. CLASS SALES(UNITS/PER)	273M	293M	309M	278M
11 PROD. CLASS SALES(DOL/PER)	514M	552M	581M	523M
12 BRAND SALES (UNITS/PER)	5.09M	5.76M	6.31M	5.59M
13 BRAND SALES (DOL/PER)	9.22M	10.4M	11.4M	10.1M
14 CONTRIBUTION (DOL/PER)	3.46M	3.91M	4.29M	3.80M
15 BRAND ADV (DOL/PER)	.486M	.606M	.876M	.414M
16 CONT. AFTER ADV(DOL/PER)	2.97M	3.31M	3.41M	3.39M
17 CUMULATIVE CONT. AFTER ADV	2.97M	6.28M	9.70M	13.1M
23 SLOPE	1.634	1.169	.241	-.379
24 BRAND DECAY CONSTANT	.048			
26 BRAND ADV. EXPONENT	2.357			
27 BRAND DEN. CONSTANT	4.333			

Table 4. Output for Groovy brand for the input shown in Table 2.

A positive SLOPE indicates that advertising increases will be profitable (in the above sense); negative, unprofitable; and zero, indifference.

2. A SEARCH option is available that permits the automatic calculation of the output for a sequence of values of any parameter in the model.

3. It is possible to print selected lines only of the output.

5.3 Applying the model.

One might think that ways to apply the model would be obvious. Not really. The model has to be worked into the system. There are a number of ways in which this can and should be done. I shall describe one which we have just been through: The model was used to assist in the quarterly review of a brand plan.

The usual pattern of operations with a consumer product is to construct a brand plan. This is done once a year. The brand plan lays out the whole marketing program in considerable detail. However, as the year progresses and various parts of the program are carried out,changes get made: new opportunities arise, actual results come in and are not quite as expected, and generally a variety of unforseen circumstances occur. Consequently, a series of review and replanning points are scheduled, usually quarterly. This does not preclude actions at other times, which in fact take place, but it does at least schedule times in which changes are definitely considered or, if already made, are consolidated in a revised forecast of results.

Our goals in applying the model were to start from a "brand plan" view of the market, modify it to accomodate the new information contained in year-to-date results, then evaluate new strategies and repredict future outcomes. Here is what we did:

<u>Step 1</u>. <u>Setting up the model according to the annual brand plan</u>. A set of input data was developed which would reproduce as model output the results found in the original brand plan. (If the brand plan had been constructed using the model, this step would not have been necessary.) The product class was identified. The seasonality and trends in product class were worked out. The input data for sales response to advertising was estimated by a combination of judgment and the examination of past time series of advertising and sales data. (In this case there were no spending levels test data but one of the side consequences of our study is that the company is seriously considering such tests for the future.) A promotion was planned for the second quarter and estimated to have a certain effect on share. A copy test, using two different areas of the country, was under way. The brand plan proposed that the test be continued for the year and so the copy index was held constant at 1.0. Similarly no substantial media changes were anticipated and the media efficiency was held at 1.0. A certain set of spending rates for advertising was envisaged and they were put into the model. A package and price change was under consideration but it did not go into the forecast.

The assembled data was put into this model and fine adjustments were made in the parameters until the model predicted the brand plan results exactly. We then took the model as a reasonable indication of the product manager's feelings about how the market worked as of the time the brand plan was written.

Step 2. Updating the model on the basis of year-to-date results. Our analysis was done after the first quarter data were in. Two principal events had occurred. First of all, sales were off from their forecast value. Second, media expenditures had been lower than originally planned. The first question to be asked was whether the lower sales could be attributed to the decreased media expenditures. Therefore, we ran the model with the new first quarter's advertising level. According to the model, the change would account for some but not all of the sales differences. The question then arose whether the advertising had a greater effect on sales than we originally thought or whether some other factors were causing sales to be off. The product manager's opinion was that other factors were probably responsible. The next question was whether the factors would continue to operate and he felt that there was no reason to believe otherwise.

Consequently we adjusted the non-advertising effects index to account for the loss in sales observed in the first quarter and not otherwise attributed to the advertising decrease. The same index was then continued through the year.

At this point it was possible to rerun the brand plan with the new parameters. It put forth a rather pessimistic view of the year.

Step 3. Evaluation of new strategies. In the meantime, a number of new strategies had been proposed. First of all, because of the lower sales in the first quarter and the implied poorer profit position, the advertising levels for the rest of the year had been reduced. Secondly, the package and price change under consideration was decided upon and scheduled to begin in the third quarter. In support of that, the trade

promotion was changed from the second quarter to the third quarter. Finally, more results were available on the copy test and a sufficient difference had shown up between the two areas that it was planned to implement the better one nationally in the fourth quarter. An estimate of the effect of the new copy on the copy index was made using the results of the test.

All these changes were made to the input. Furthermore a rough brand plan for the following year was put into the analysis. Then the new plan was run. This suggested there would be a substantial improvement in sales and profit compared to the previous case. It also showed that certain reallocations of advertising spending during the year and certain changes in the budget might well be warranted. These changes were implemented.

Step 4. Predictions of Future Results. After the above runs were made a few further adjustments to strategy were decided upon. Thus the whole plan was run again. This run then became part of the quarterly review.

The above application illustrates the general way we expect the model to enter into the product manager's operation.

6. What about science?

The discussion so far seems to have ignored the traditional goals and criteria of science. We have passed over issues like: How does the world really work? What is the best way to describe the world in a model? How accurate is a given model? How do we measure accuracy?

Clearly these are important issues, although there is an extreme and fairly tenable position that says we can gain value from models, even if they do not contain real world measurements. The argument is that a quantitative model can be used as a qualitative device to aid qualitative thinking. In this role there is no need for a one-to-one correspondence between real world quantities and quantities in the model. Moran [4], for example, makes this point.

However, that is not the intention here. We aspire that the model represent the world well. However, the standard of comparison will not be perfection but rather what the manager has available to him now. If you look at his present situation you find that he has practically no predictive models beyond simple extrapolation of the past, so that complex models and detailed fidelity are not yet required.

In this connection let me express some discomfort with the currently popular phrase "model validation." Validity means truth. You don't have to validate your model on my account - I know it is false. The real issue is usually accuracy and the process might better be called evaluation.

Most of the models we are proposing here tend, at least initially, to be over parameterized with respect to the available data. That is, we tend to put in more phenomena than we know how to measure, but do so anyway because we believe they are important. As a result, by suitably picking parameters we can often fit past data fairly easily. Therefore it may be difficult to develop a good a priori measure of the accuracy of the model.

We should, however, evaluate the model by tracking performance, if this is at all applicable. As decisions are made, we usually forecast the future with the model. We should see whether actual differs from this forecast. Ordinarily it will. Then the task is to determine why and correct the model parameters or perhaps even the model structure. This process will be greatly facilitated if the model contains a variety of touch points with the real world, i.e. contains quantities which are observable in the real world. The process will also be aided if we design and implement special measurement programs. One of the most obvious side benefits of model use is the pinpointing of critical measurements that should be made.

The task of parameterizing the model is, of course, difficult and important. A good methodology for this is the one used by Scott Armstrong [5] in forecasting of camera sales. After he had specified what he hoped was a satisfactory structure, he proceeded as follows: First, all the parameters were set by judgment. Then, he tried to estimate each through data analysis. He used as many independent data sets and approaches to analysis as he could invent and separately appraised the accuracy of each. Incidentally, the a priori estimates were often quite similar to those obtained by data analysis. Then he combined the results up to that point by formal methods. Using the now parameterized model, he made forecasts and devised various means of evaluating their quality. One way was to make forecasts from new data. Having done this, he readjusted his parameters to use the information from the new data. The same sequence of initial parameterization, model use, new data

collection, and updating the parameters is an adaptive procedure appropriate for most applications of models to on-going operations.

7. Discussion

The three product managers we have been working with have each responded in different ways. All have been interested and very eager about trying the model on their brands. One has developed an excellent grasp of what we are doing and is an important source of model ideas. Another has spent considerable time working with the model in cooperation with another man at his company. Together they have developed the application discussed earlier. That work is clearly affecting operations. In the third case, we entered the scene just as the product manager was struggling with an advertising budget problem. In a crash program we put together data and made several runs. These certainly affected his recommendations. However, I do not feel that he has yet made the model his own. We are continuing with all three and plan to add at least one more shortly.

Although it is really too early to tell, I would like to predict how the model will enter these companies and how the companies will organize to make use of it. First of all, the product managers will have to learn how to use the model. This requires technical assistance and a teaching program. Technical assistance is required for problem formulation and data analysis. As for a teaching program, our experience suggests that the best approach is to lead the potential user through a sequence of models of increasing scope and complexity. This is essentially what we have done with ADBUDG and it is exactly what Glen Urban does with

his SPRINTER [3] new product model. Often a user, having learned a simple model, will start to ask for just the additional considerations found in the advanced models.

As for organization, the matrix form seems best. Under this set-up the product manager has line responsibility but also has a commitment from operations research and/or market research in terms of somebody assigned to his product. The product manager needs a person to whom he can address questions about model behavior and a person who can help design measurements and do data analysis.

One of the most evident consequences of the model is that it is a stone in the shoe for better data. Under present planning procedures, many measurement problems are glossed over or suppressed. The model faces explicit consideration of every factor it contains and so pinpoints data needs.

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